Chapter 18
Corporate Environmental Sustainability and DEA

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Abstract Data envelopment analysis (DEA) is a flexible management tool and methodology that can be utilized in a variety of ways. This flexibility is evident in the applications of DEA for investigating corporate environmental sustainability and management. In this chapter an overview of DEA and how it can be utilized alone and with other techniques to investigate corporate environmental sustainability questions is presented. Discussion on how DEA has been used for environmental sustainability theory development and testing using empirical information makes up a core aspect of some of the major contributions DEA has provided in this field. DEA is also used as a management decision support tool, which includes benchmarking and multiple criteria decision making. Some details on how each was used with exemplary references are included. Some future DEA directions that could be used for research and application in corporate environmental sustainability is also defined.

Keywords Data envelopment analysis • Greening • Environmental • Business • Benchmarking • Decision making

18.1 Introduction

Data envelopment analysis (DEA) has seen many years of application on issues related to organizational environmental sustainability in general and environmental performance in particular. Although emerging from the economics literature as a production frontier methodology with the traditional economic efficiency of outputs generated from inputs, DEA has expanded in perspective and application. The use of DEA has expanded as a descriptive analysis tool, to generate data for statistical analysis and inferencing, and as a prescriptive decision support tool for organizational decision making.

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In this chapter we present how some literature investigates corporate environmental sustainability. Much of the work reviewed here focuses on DEA based developments and research by the author of this chapter and some of the lessons learned. A summary of these investigations and future research is also presented. The discussion will focus on the application and usefulness of the DEA tools. Mathematical modeling of the DEA models, many of which are covered elsewhere in this book, will not be detailed. Only general presentation of the DEA-based models is discussed. Individual DEA models and joint application with supporting synergistic tools are also mentioned without delving too deeply in to the mathematical notation and development. The original papers provide a better and detailed exposition of the reviewed models and papers.

Thus, a descriptive and applied perspective will be the methodological approach used in this chapter.

18.2 Corporate Environmental Sustainability

Concerns about industrial and commerce related environmental issues have increased over the years. The reasons for this concern are manifold and range from social, scientific, and technological developments over the years to various specific regional and global pressures faced by these organizations. Social media, instant communication, advances in science, evolving regulatory have all contributed to this increased knowledge and pressures by citizens, communities, regulators, competitors, and consumers.

The science around some of today's environmental problems has been critical in convincing society and organizations that the concerns are real and require some form of alteration on practices. Two areas where this is especially true are in the depletion of natural resources, necessary for continual production, and climate change. Socially, there is greater awareness throughout the world, especially in emerging nations such as China, India, and Brazil, that we must do more to protect ourselves and our environment. As the world continues to develop economically, environmental burdens and their impact on quality of life have raised social awareness. Communications technology, such as the internet and social media, have made environmental information and social communication easier to access than at any other time in history. New regulations that are flexible and voluntary, sometimes supported with market mechanisms or incentives are becoming more evident and putting organizations in unique positions to more carefully respond to them. Finally, industrial self-regulation for corporate social responsibility through certifications, eco-labels, and industrial best practices are also becoming more evident.

The response by industry has not only been from a risk and liability reduction perspective with only a focus on minimizing negative regulatory exposure, but also from more competitive and business case reasons. One of the major reasons that organizations seek to implement practices and technology to reduce ecological footprints is because it can save costs. This win-win opportunity of lowering costs arises when waste is eliminated from a system. This joint gain arises from building organizational 'eco-efficiency'. Eco-efficiency is closely aligned with general efficiency in seeking to minimize inputs and bad outputs, while maximizing good outputs (Dyckhoff and Allen 2001; Egilmez and Park 2014). Usually waste is considered a bad output and seeking to be minimized. Waste can be solid, gaseous, or liquid. Clearly, measuring and evaluating efficiency, eco-efficiency or otherwise is a DEA goal.

In addition organizations may wish to make investments associated with improving environmental sustainability performance. DEA can be effectively be used in this situation as a multiple criteria decision tool (Sarkis 2000a; Gonzalez et al. 2015). Thus, if an organization seeks to make a selection decision it would consider multiple dimensions including environmental, economic, and business dimensions.

Given that DEA is valuable for performance measurement. It can simplify multiple dimensions to a smaller set of performance metrics. Corporate environmental sustainability and green supply chains are both examples of situations where performance measurement has gained in interest and importance.

From a research perspective DEA can be used to evaluate large sources of data for empirical relationships and statistical inferencing. The research questions may be directly related to DEA outputs to determine if there are differences in efficiency scores or as dependent or independent variables of standard econometric approaches.

Each of these DEA-based applications with example situations and references are now overviewed. Additional resources for application of DEA for corporate environmental sustainability topics do exist (e.g. see Sarkis and Talluri 2004a, for additional examples).

18.3 Theory Testing and Statistical Inferencing with DEA: An Environmental Perspective

DEA results may be statistically evaluated and this approach is valuable for broader theoretical or econometric evaluation. The major difficulty with DEA data is that it does not necessarily fall within some of the distribution requirements assumed by various statistical inferential tools. Thus, there is a reliance on non-parametric statistical inferential techniques.

Results of DEA are typically relative efficiencies for organizations or units within organizations. These efficiency scores can then be used to evaluate theory using non-parametric statistical techniques. The major non-parametric tools that have been identified by the literature are based on ranking statistics. The two models that are specifically recommended by Sarkis (2000a, b) are the Mann-Whitney U-test and the Kruskal-Wallis rank tests.

Some of the theory testing from a corporate sustainability perspective has included evaluating waste management location analysis as a comparative analysis with other multiple criteria decision tool to determine if rank orders were similar (Sarkis 2000a). In this situation, Kendall's Tau-b test was utilized to evaluating of the rankings by outranking and DEA approaches were statistically similar. The methodology utilized a weight constrained DEA approach and found that the more constrained the DEA model, based on relative importance considerations, the better the match to the outranking approaches.

18.3.1 Financial and Environmental Performance Relationship

In the above approaches a direct ranking relationship and determining whether significant differences were completed using univariate tests. For more advanced econometric testing the utilization of multivariate techniques would be more appropriate. In this situation a number of variations using DEA were utilized.

A direct approach of using DEA to determine environmental efficiency with the U.S. environmental protection agency's toxics releases inventory was used as an independent variable for the following relationship test (Sarkis and Cordeiro 2001):

$$\begin{aligned}&\text{Firm short-run financial performance}\\&\quad = \mathrm{f}(\text{Environmental efficiency; firm size; firm leverage; error})\end{aligned}$$

In this situation the statistical and theoretical examination focused on whether a relationship existed between firm environmental efficiency and short-run financial performance. This relationship is probably one of the most studied and focuses on whether 'doing good', on environmental performance is related to 'doing well' economically. The selection of the input and output variables in this case were focused on altering the DEA model where one model focused on pollution prevention efficiency, and the other model focused on end-of-pipe efficiency. The theoretical proposition was that stronger relationships would exist with pollution prevention.

The efficiency measures utilize a time difference approach. Where previous year's data was compared to current year data to show improvements in performance.

18.3.2 Ecological Efficiency and Technological Disposition Relationship

An ecological modernization perspective (Sarkis and Cordeiro 2009, 2012) argues that technology can help countries and organizations separate economic growth from environmental degradation. Ecological modernization theory began as a broad-based national policy instrument, but has been discussed as an opportunity for industry and individual organizations. This theory sets the foundation for investigating the relationship between technological choices and ecological and/or economic efficiency. For example, the empirical evaluation can be completed using the following empirical relationship for efficiency at the electrical plant level.

$$\begin{aligned} \mathit{Plant\,Efficiency} = {} & b0 + b1(\mathit{Average\,Generator\,age}) \\ & + b2\,(\mathit{Utility\,Ownership}) + b3\,(\mathit{Plant\,operates\,Scrubber}) \\ & + b4\,\big(\mathit{Plant\,usesGas\,Fuel}\big) + b5\,(\mathit{Plant\,Uses\,Coal\,Fuel}) \\ & + b6\,\big(\mathit{Plant\,Used\,FGD\,Scrubber\,Technology\,to\,Comply}, \text{``}\mathit{End\,of\,Pipe}\text{''}\big) \\ & + b7\,(\mathit{Plant\,Purchased\,Credits\,to\,Comply}) \\ & + b8\,(\mathit{Plant\,Changed\,Fuels\,or\,Fuel\,Blend}, \text{``}\mathit{In\text{-}Process}\text{''}) \\ & + b9\text{-}18\,(\mathit{Location}, \mathit{Regions}\,1\text{-}9, 11) + \mathit{error} \end{aligned}$$

The inputs and outputs for these models can be altered to identify ecological versus technical (business) efficiency, which is the dependent variable in this empirical relationship.

The methodologies for each paper, although the data and theory were similar, had variations in the types of DEA models used and multivariate regression analysis.

A variety of DEA models can be used to evaluate the efficiency. One characteristic that I typically choose are DEA models that may have a broader variation in efficiency scores. That is, efficiency scores that are not truncated at either 1 or at 0. One such model is the Tchebycheff radius DEA model (Rousseau and Semple 1995). The efficiency scores in this situation can take on a continuous positive and negative number values. In these situations, undesireable outputs (e.g. pollution effluents) were just treated as inputs into the system, where lessening of undesireable outputs was a goal similar to inputs when seeking to create greater efficiency. Another DEA model used to help reduce the issue of truncation was the superefficiency slack based model (Cooper et al. 2007).

The resulting conclusions of these studies were that the inclusion and consideration of ecological factors into performance evaluation by organizations can significantly change how organizations view operational and investment decisions. A complete analysis of goods and bads from a technical and ecological efficiency perspective rather than from the perspective of technical efficiency alone may alter management's perspectives on their operational decisions.

Another version of DEA models that is very popular in environmental efficiency modeling is the use of bad inputs and outputs that may be separable or inseparable (Cooper et al. 2007). This was the model used in the second in the series on ecological modernization (Sarkis and Cordeiro 2012). The theory was also focused on whether more proactive measure would be better suited for overall and technical efficiency. The separable-non-separable factors in inputs and outputs were meant to determine which factors were more closely and directly aligned. For example boiler heat was directly related to emissions, but boiler capacity may be more separable and not as directly correlated with emissions. This modeling allows bad outputs to remain as outputs.

The multivariate regression analysis utilized Tobit regression when the Tchebycheff radius methodology and slack-based superefficiency models were used (Sarkis and Cordeiro 2012). This usage occurred even though the only truncation of data occurred in the slack-based model. It is acknowledged that the use of second-stage explanatory regression models in DEA, while frequently employed, continues to be viewed by some as controversial. If suitable alternatives are non-existent for second stage multiple regression analysis of DEA results (e.g. including all variables in a DEA model), the use of truncated multiple regression approaches may be the only alternative. Other techniques to overcome some of the correlation issues have been recommended (Simar and Wilson 2007).

18.3.3 Environmental Practices, Performance and Risk Management

Many organizations seek to adopt environmental practices to help reduce risks. This risk management perspective requires that organizations consider how to minimize risks by reducing hazardous waste materials, liability exposure, and improved human health. In fact, much of the U.S. Environmental Protection Agency programs have to do with limiting human health exposure with respect to environmental issues.

In one study (Sarkis 2006) that considered these relationships a series of questions relating to when and what was adopted in risk management and environmental practices were compared to environmental performance. The research questions were general and included:

1. Are earlier adopting organizations better environmental performers, and do they adopt more environmental and risk management programs and practices?
2. Is there a positive relationship between better current environmental performers and adoption of environmental practices?
3. Is there a positive relationship between organizations that improve their environmental performance over time and the amount of environmental and risk management programs adopted?

4. Should organizations adopt more environmental and risk management programs?

To test various hypotheses that seek to answer the above questions, this paper provided two different modeling approaches. First, it varied the input and output measures to determine the specific type of environmental performance that was to be evaluated. Also, variations in the type of DEA model were also used.

Unlike the undesireable outputs approaches described in the previous sections (e.g. making the outputs inputs, or having a different negative valuation in slack-based approaches) this study rescales the undesireable outputs. The rescaling was completed by taking the largest value for each of the outputs and subtracting the value for each facility from this large value. Thus, with this rescaling a larger value is considered to be better, as is the requirement for output data.

The Mann-Whitney U non-parametric independent samples test was used to evaluate a number of hypotheses. This is unlike the use of multivariate regression models. To be able to complete this analysis two groups were formed those that had various factor above and below average valuations and then the inference test was utilized based on efficiency scores and whether statistically significant differences occurred.

18.4 Benchmarking and Key Performance Indicators with DEA

In practice and application, DEA can be used to help organizations complete benchmarking and performance evaluation. DEA as a benchmarking tool can help identify organizational environmental performance and eco-efficiency weaknesses and to address those issues. Alternatively, it can help organizations identify best practices that can be diffused throughout the organizations. Benchmarking and performance measurement are ways that managers can continuously improve their operations. Using DEA as a performance measurement and benchmarking tool has become commonplace (Zhu 2014).

External benchmarking using DEA has typically been on financial or marketing performance and measures, for example with the banking industry. Internal benchmarking has also been developed for internal process improvement. Benchmarking using DEA has been used with respect to the envelopment side of the ratio based linear programming formulation. That is, the units that have a positive efficiency score form the facet set and are regarded as the benchmark DMUs. In other words, it is these DMUs that should be benchmark partners for the organization that wishes to improve its operations.

Benchmarking using DEA may not just be focused on using the facet sets from DEA based models. Another approach that may be useful is through identification of weights used for identifying efficient units in the objective function. Unfortunately, this is not a guaranteed approach since DEA models can generate alternative weight sets for the optimal efficiency score. But, if weights are to be used, various clustering approaches of weights can identify benchmark partners and groups (e.g. Sarkis and Talluri 2004b).

Using fossil fuel electricity generating utilities benchmarking across plants was completed using DEA and clustering approaches (Sarkis 2004). This study evaluated the eco-efficiencies of the top 100 major U.S. fossil-fueled electricity generating plants from 1998 data. The efficiency scores were treated by a clustering method in identifying benchmarks for improving poorly performing plants. Efficiency measures were based on three resource input measures including boiler generating capacity, total fuel heat used, and total generator capacity, and four output measures including actual energy generated, SO2 (sulfur dioxide), NOx (nitrous oxide), and CO2 (carbon dioxide) emissions. The benchmarking was completed to show some characteristics of the benchmarked plants and groups. These characteristics may or may not be in control of management but could provide insights into what may contribute to various performance characteristics of DMUs (plants). Cross efficiency approaches can also be applied in these circumstances to help identify averaged solutions (Talluri and Sarkis 1997, 2002).

The organizational supply chain is an important and emergent area of benchmarking for organizational environmental sustainability (Yakovleva et al. 2012). Although much of the current focus on supply chain sustainability is on the dyadic relationship, extensions to multiple tiers of the supply chain and identifying critical success factors is a recent area of research (Grimm et al. 2014). Benchmarking individual dyads or multiple tiers from sustainable supply chain perspective, in itself, is a complex issue. Not only can their multiple dimensions of business and activities in the supply chain.

The supply chain operations reference (SCOR) model is an example of the complexity and variety of measures that can be used for benchmarking supply chains in general. The SCOR model categorizes the processes of five supply chain stages: plan, source, make, deliver and return. Within each of these stages there SCOR categorizes performance measures on cost, time, quality, flexibility, and innovation dimensions (Bai et al. 2012). Adding these dimensions environmental factors to economic and business factors only adds to the complexity. The literature has accepted the multidimensional and complex relationships of supply chain sustainability performance evaluation (Varsei et al. 2014). Given the potentially large data sets and the need to capture all this data, finding the best, key performance, metrics for sustainable supply chains requires significant development and thought. DEA alone, or with other tools, can provide some important answers. Identifying the most pertinent data in terms of additional information provided by the data may be a way of limiting the complexity.

Along this track, the use of rough set theory, an information set theory methodology for data mining, along with DEA can provide a tool for helping to filter and identify key performance indicators (Bai and Sarkis 2014). The results show that key performance indicators can be determined using neighborhood rough set by reducing overlapping and closely related performance metrics. DEA performance results provide insight into relative performance, benchmarking, of suppliers.

The supply chain sustainability performance results from both the neighborhood rough set and DEA can be quite sensitive to the parameters selected and sustainability key performance indicator sets that were determined. Thus, careful monitoring of using these joint tools may still be required. Although, the use of rough set and DEA can greatly reduce the number of metrics and measures that are needed in this complex environment.

Advances in DEA for supply chain management may include network based techniques to complete benchmarking and decision making associated with sustainability and supply chains (e.g. Chen and Yan 2011; Aviles-Sacoto et al. 2015).

18.5 Multiple Criteria Decision Making with DEA

DEA as a singular approach or jointly with other approaches can be effectively applied to decision making contexts. Decisions facing corporate sustainability and environmental contexts, as mentioned in the previous section are complex. DEA is a tool that can help with data mining and simplifying complex and multiple dimensions to a single or smaller subset of dimensions can prove helpful for decision making.

DEA can be used effectively as a multiple criteria decision making tool (Cook et al. 2014; Doyle and Green 1993; Sarkis 1997, 1999; Sarkis and Talluri 1999). The evaluation of environmental projects or programs is one application of the various DEA models. Since environmental technology and programs are typically strategic, the use of multiple factors and complex factors is standard practice. These multiple factors may include tangible and intangible characteristics. DEA is suitable for this mixture of criteria and factors. With the DEA ranking approaches available, the decision making for these programs become clear. Managerial information can be integrated with these approaches by introducing weight limitation constraints, also defined as cone ratios and assurance regions (Sarkis 1999). This flexibility in DEA allows for a number of ways that ranking and multiple criteria techniques can be used. Clearly, one of the limitations of this set of models is that only deterministic and discrete alternatives can initially be considered since the decision objects and alternatives are typically the DMUs.

In this context DEA can be used as a valuable managerial decision tool. For example DMU's can be various environmental technologies that an organization needs to investigate for potential adoption, or selection of suppliers based on environmental sustainability criterion (Mahdiloo et al. 2015). The criteria may be represented as inputs and outputs. Typically, in a multiple criteria decision making environment, criteria that improve as their value decreases (e.g. cost, emissions) may be considered inputs. For criteria that improve as their values increase (e.g. energy delivered) these would be considered outputs in a DEA model. The results can then be analyzed from a ranking perspective, assuming that there is ample discrimination amongst the efficiency scores of the DEA methodologies.

DEA techniques that are good discriminators are more valuable for selection decisions. Thus, the use of a number of approaches could be considered as more preferable techniques. Although care should be taken in the selection of the technique, since in many cases the final rankings are not always similar. A portfolio selection approach (where sets of environmental decisions are to be made) may also give different groupings of best choices depending on the technique. To overcome these discrepancies additional decision tools or other factors can be considered in final evaluations, or some form of portfolio score can be determined. These are issues that require additional investigations.

18.5.1 Justifying and Choosing Environmental Technologies

One very important multiple criteria decision making analysis approach is the justification, selection and management of environmental technologies. Environmental technologies and innovations can be defined broadly. One set of technologies can include standard hard, tangible technologies, such as scrubbers for end-of-pipe solutions in the utility industry or purchase of solar panels for renewable energy generation (Sarkis and Tamarkin 2005; Sarkis and Cordeiro 2009, 2012). There are softer environmental technologies such as green information systems and software to help in planning and design of environmentally sound products (Bai and Sarkis 2013). Examples would include life cycle analysis tools and computer aided design systems for ecological design of products. Another innovation or technology category may include control technologies that help monitor and address environmental sustainability issues (Sarkis and Weinrach, 2001). These tools and technologies can be software or hardware oriented as well, but help to manage processes by limiting emissions or quality and scrap of materials during processing. They may also provide information to help manage environmental sustainability such as with smart grids and energy reporting (Bai and Sarkis 2013; Sarkis et al. 2013). One additional set of organizational technologies are organizational process innovations. For example environmental management systems and standards such as ISO 14000 may be considered organizational technological innovations. Inter-organizational innovations would be various green supply chain practices (Zhu et al. 2012).

A couple of ways to help filter the decisions and incorporate managerial preference is through the integration of DEA with other decision tools such as the analytical hierarchy process (AHP) or analytical network process (ANP) (Saaty 1996) and multiattribute utility theory (Keeney and Raiffa 1976), may help management filter to a better solution. As mentioned earlier managerial preferences for criteria may help restrict the weights (or relative weights) that are given to each of the criteria. One approach of completing this step is by adding assurance regions (AR).

The concept of AR is described in detail by Thompson et al. (1990). AR requires a definition of upper and lower bounds for each input and output weight. The upper and lower bounds for each weight can help define constraints that relate the weight values, and potentially managerial importance values, of various factors. A simple example for defining the AR constraints for two input weights v1 and v2 is initiated by setting lower (LB) and upper bounds (UB) on each weight. These LB and UB may be ranges for preference weights for each of the criteria from the decision makers. The AR constraints relate the weights and their bounds to each other.

These constraints can be added to various DEA models directly. If the upper and lower bounds of the weights for all the factors are known with certainty, or have exact agreement among managers, and do not need a range to define them, the AR constraints would be equalities. From a computational perspective additional constraints may slow the procedure down. For examples of this application using AHP to limit the weights see Sarkis (1997, 1999).

Various factors for decision making in this environment may be mixed and incorporate business and environmental sustainability dimensions. For example, Cost, Quality, Recyclability, Process Waste Reduction, Packaging Waste Reduction, and Regulatory Compliance may all be decision factors that influence the selection of an environmentally significant technology (Bai and Sarkis, 2012; Sarkis and Dijkshoorn, 2007). The first two factors, Cost and Quality, would be considered standard business performance measures that may be used to evaluate any program or project within an organization. The remaining measures are those that focus primarily on the environmental operations and manufacturing characteristics. These environmentally based factors cover a spectrum from reactive environmental measures (e.g. Regulatory compliance) to proactive measures (e.g. process waste reduction). There may be many more factors that could be considered, as evidenced in the benchmarking discussion. Some filtration process, e.g. using information theoretic approaches, may allow for some initial evaluation of the factors that eliminates less important ones and considers these factors as the primary ones that should be used to evaluate these programs.

Others have applied multiattribute utility theory (MAUT) approaches and ANP as data generators for DEA data. Using these approaches to help generate data can overcome some of the difficulties of qualitative data while incorporating managerial preferences. Thus, the ordering of methodologies, DEA/ANP/MAUT can work interchangeably in terms of developing and implementing various measures for multiple criteria decision making.

18.6 Future Research Directions

Given the hundreds of variations and developments in DEA there remains ample opportunity for utilizing these tools for further investigations. Multi-tier and network DEA can be utilized to investigate sustainable supply chain issues that allow for consideration of multiple levels of supply chain tiers. The field of multi-tier sustainable supply chains is very much in its infancy and even the most basic models can make a contribution to the body of knowledge in corporate environmental sustainability. The difficulty arises in finding practical data and examples. The integration of DEA with life cycle analysis data may be the most appropriate approach to link the two techniques. Although some modeling has been completed to link DEA and life cycle assessment, the analysis is still for a single stage in the supply chain.

Many applications of DEA and corporate eco-efficiency and environmental sustainability research has focused on traditionally polluting and industrial organizations. Service organizations can also have significant environmental sustainability implications. DEA has been effectively applied for service organization performance (Sherman and Zhu 2013). Identification of various environmental measures in this context is important and may include various energy and materials waste aspects. For example, information technology plays a big role in service organizations and greening information technology investigations using DEA with empirical, benchmarking and decision making approaches is a fertile area for research and application.

Bootstrapping of information and data with application to DEA may be helpful when data is not available to make a complete analysis or requiring some form of discrimination amongst DMUs. Bootstrapping methodologies to help randomly generate data based on current data availability and characteristics is an important aspect of DEA that has significant room for application in environmental sustainability management within organizations. Although Lothgren (1998)) describes and evaluates alternative DEA-based bootstrapping estimation, which can be used in these studies, other techniques do exist. For example, the use and application of Bayesian analysis based simulation procedures to generate data and their impact on DEA is a potential bootstrapping approach which is a fruitful direction for future research. Currently, some modeling using Bayesian for sustainable supplier selection has been applied (Sarkis and Dhavale 2015), expanding these valuations with an integration of DEA as a benchmarking or MCDM tool could be a multiple methodological extension that can address some of the limitations of data generation and analysis.

Comparing and contrasting DEA with other productivity analysis approaches in environmental programs provides another opportunity for research. Evaluation using stochastic frontier analysis (SFA) and DEA can be investigated from an environmental perspective. One study (Cordeiro et al. 2012) found that results may be relatively similar, which bodes well in validating some of the DEA techniques. This methodological finding provides confidence in the pattern of results, since the approach and assumptions utilized in SFA complement those of the DEA approach. The technique was applied for environmentally oriented dimensions, comparing and contrasting to a variety of DEA under various experiments can provide insights into limitations and sensitivity of DEA in these contexts.

Multiple stages of evaluation, as in supply chain management stages with multiple organizational levels, can also be considered for temporal factors. Time based panel data to test the evolution of environmental sustainability across industries and time is a fertile area for model development, applications, and theoretical study. Basic questions that can be answered include whether organizations can and do become more efficient in their environmental sustainability efforts over time and also whether different industries make more rapid gains in environmental sustainability over time. Moreover the role played by salient environmental practices such as environmental auditing, waste monitoring, environmental policies and other support practices for improving sustainability in organizations and across supply chains is well worth investigating (Bai and Sarkis, 2012).

The further integration of DEA with a broad variety of methodologies can still be completed. Multiple criteria tools such as TOPSIS, VIKOR, and Outranking, along with various data mining tools related to entropy and information theory, can also be avenues for multi-methodological integration. An important application is to be able to aid in decision making and management of the extant environmental sustainability performance measures that exist.

The use of DEA for quantitatively oriented corporate environmental sustainability information has been well developed. Extending DEA and research to incorporate less tangible measures, such as reputation and image outcomes or programmatic characteristics, may require some adjustment or development of categorical DEA methodologies. Extensions of research to include social sustainability in organizational and supply chain activities are another important direction for research (Brandenburg et al. 2014). Broader organizational and supply chain sustainability investigation that incorporate social sustainability performance measures may also benefit from models that incorporate intangible characteristics. Social sustainability is more likely to incorporate intangible dimensions such as equity, child labor, and diversity issues that are difficult to measure.

18.7 Conclusion

DEA has had a substantial history as a tool to investigate organizational environmental sustainability. It has proven valuable for the understanding and advancement of practice in this field from the perspective of theory evaluation and development, managerial decision making, and organizational benchmarking. Whether as a stand-alone tool or with other methodologies insights gained have been very valuable. DEA is especially beneficial because the complexities involved in understanding and managing sustainability can be effectively addressed.

Further investigations are warranted and DEA as a tool can help us make our organizations more thoughtful, efficient, and sustainable, not only for this generation but for future generations. Hopefully this chapter helps provide insights to old and new researchers to further advance study in this critically important study.

References

Aviles-Sacoto, S., Cook, W. D., Imanirad, R., & Zhu, J. (2015). Two-stage network DEA: When intermediate measures can be treated as outputs from the second stage. *Journal of the Operational Research Society, 66*(11), 1868–1877.

Bai, C., & Sarkis, J. (2012). Performance measurement and evaluation for sustainable supply chains using rough set and data envelopment analysis. In T. Boone, V. Jayaraman, & R. Ganeshan (Eds.), *Sustainable supply chains* (pp. 223–241). New York: Springer.

Bai, C., & Sarkis, J. (2013). Green information technology strategic justification and evaluation. *Information Systems Frontiers, 15*(5), 831–847.

Bai, C., & Sarkis, J. (2014). Determining and applying sustainable supplier key performance indicators. *Supply Chain Management: An International Journal, 19*(3), 275–291.

Bai, C., Sarkis, J., Wei, X., & Koh, L. (2012). Evaluating ecological sustainable performance measures for supply chain management. *Supply Chain Management: An International Journal, 17*(1), 78–92.

Brandenburg, M., Govindan, K., Sarkis, J., & Seuring, S. (2014). Quantitative models for sustainable supply chain management: Developments and directions. *European Journal of Operational Research, 233*(2), 299–312.

Chen, C., & Yan, H. (2011). Network DEA model for supply chain performance evaluation. *European Journal of Operational Research, 213*(1), 147–155.

Cook, W. D., Tone, K., & Zhu, J. (2014). Data envelopment analysis: Prior to choosing a model. *Omega, 44*, 1–4.

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). *Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software*. New York: Springer.

Cordeiro, J. J., Sarkis, J., Vazquez-Brust, D., Frater, L., & Dijkshoorn, J. (2012). An evaluation of technical efficiency and managerial correlates of solid waste management by Welsh SMEs using parametric and non-parametric techniques. *Journal of the Operational Research Society, 63*(5), 653–664.

Doyle, J., & Green, R. (1993). Data envelopment analysis and multiple criteria decision making. *Omega, 21*(6), 713–715.

Dyckhoff, H., & Allen, K. (2001). Measuring ecological efficiency with data envelopment analysis (DEA). *European Journal of Operational Research, 132*(2), 312–325.

Egilmez, G., & Park, Y. S. (2014). Transportation related carbon, energy and water footprint analysis of US manufacturing: An eco-efficiency assessment. *Transportation Research Part D: Transport and Environment, 32*, 143–159.

Gonzalez, E. D., Sarkis, J., Huisingh, D., Huatuco, L. H., Maculan, N., Montoya, J., et al. (2015). Making real progress toward more sustainable societies using decision support models and tools: Introduction to the special volume. *Journal of Cleaner Production, 105*, 1–13.

Grimm, J. H., Hofstetter, J. S., & Sarkis, J. (2014). Critical factors for sub-supplier management: A sustainable food supply chains perspective. *International Journal of Production Economics, 152*, 159–173.

Lothgren, M. (1998). *How to bootstrap DEA estimators: A Monte Carlo comparison* (WP in Economics and Finance, 223).

Mahdiloo, M., Saen, R. F., & Lee, K. H. (2015). Technical, environmental and eco-efficiency measurement for supplier selection: An extension and application of data envelopment analysis. *International Journal of Production Economics, 168*, 279–289.

Keeney R. L. & Raiffa H. (1976). Decisions with Multiple Objectives. J. Wiley & Sons, New York.

Rousseau, J. J., & Semple, J. H. (1995). Radii of classification preservation in data envelopment analysis: A case study of 'Program Follow-Through'. *Journal of the Operational Research Society, 46*, 943–957.

Saaty, T. L. (1996). Analytical network process. Pittsburgh: RWS Publications.

Sarkis, J. (1997). Evaluating flexible manufacturing systems alternatives using data envelopment analysis. *The Engineering Economist, 43*(1), 25–47.

Sarkis, J. (1999). A methodological framework for evaluating environmentally conscious manufacturing programs. *Computers & Industrial Engineering, 36*(4), 793–810.

Sarkis, J. (2000a). A comparative analysis of DEA as a discrete alternative multiple criteria decision tool. *European Journal of Operational Research, 123*(3), 543–557.

Sarkis, J. (2000b). An analysis of the operational efficiency of major airports in the United States. *Journal of Operations Management, 18*(3), 335–351.

Sarkis, J. (2004). Environmental benchmarking of the largest fossil-fueled electricity generating plants in the US. In *Photonics Technologies for Robotics, Automation, and Manufacturing* (pp. 182–192). Massachusetts: International Society for Optics and Photonics.

Sarkis, J. (2006). The adoption of environmental and risk management practices: Relationships to environmental performance. *Annals of Operations Research, 145*(1), 367–381.

Sarkis, J., & Cordeiro, J. J. (2001). An empirical evaluation of environmental efficiencies and firm performance: Pollution prevention versus end-of-pipe practice. *European Journal of Operational Research, 135*(1), 102–113.

Sarkis, J., & Cordeiro, J. J. (2009). Investigating technical and ecological efficiencies in the electricity generation industry: Are there win-win opportunities? *Journal of the Operational Research Society, 60*(9), 1160–1172.

Sarkis, J., & Cordeiro, J. J. (2012). Ecological modernization in the electrical utility industry: An application of a bads–goods DEA model of ecological and technical efficiency. *European Journal of Operational Research, 219*(2), 386–395.

Sarkis, J., & Dhavale, D. G. (2015). Supplier selection for sustainable operations: A triple-bottom-line approach using a Bayesian framework. *International Journal of Production Economics, 166*, 177–191.

Sarkis, J., & Dijkshoorn, J. (2007). Relationships between solid waste management performance and environmental practice adoption in Welsh small and medium-sized enterprises (SMEs). *International Journal of Production Research, 45*(21), 4989–5015.

Sarkis, J., Koo, C., & Watson, R. T. (2013). Green information systems & technologies—This generation and beyond: Introduction to the special issue. *Information Systems Frontiers, 15*(5), 695–704.

Sarkis, J., & Talluri, S. (1999). A decision model for evaluation of flexible manufacturing systems in the presence of both cardinal and ordinal factors. *International Journal of Production Research, 37*(13), 2927–2938.

Sarkis, J., & Talluri, S. (2004a). Ecoefficiency measurement using data envelopment analysis: Research and practitioner issues. *Journal of Environmental Assessment Policy and Management, 6*(1), 91–123.

Sarkis, J., & Talluri, S. (2004b). Performance based clustering for benchmarking of US airports. *Transportation Research Part A: Policy and Practice, 38*(5), 329–346.

Sarkis, J., & Tamarkin, M. (2005). Real options analysis for "green trading": The case of greenhouse gases. *The Engineering Economist, 50*(3), 273–294.

Sarkis, J., & Weinrach, J. (2001). Using data envelopment analysis to evaluate environmentally conscious waste treatment technology. *Journal of Cleaner Production, 9*(5), 417–427.

Sherman, H. D., & Zhu, J. (2013). Analyzing performance in service organizations. *Sloan Management Review, 54*(4), 36–42.

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics, 136*(1), 31–64.

Talluri, S., & Sarkis, J. (1997). Extensions in efficiency measurement of alternate machine component grouping solutions via data envelopment analysis. *IEEE Transactions on Engineering Management, 44*(3), 299–304.

Talluri, S., & Sarkis, J. (2002). A model for performance monitoring of suppliers. *International Journal of Production Research, 40*(16), 4257–4269.

Thompson, R. G., Langemeier, L. N., Lee, E., & Thrall, R. M. (1990). DEA sensitivity analysis of efficiency measures with an application to Kansas farming. *Journal of Econometrics*, *46*(1), 2.

Varsei, M., Soosay, C., Fahimnia, B., & Sarkis, J. (2014). Framing sustainability performance of supply chains with multidimensional indicators. *Supply Chain Management: An International Journal, 19*(3), 242–257.

Yakovleva, N., Sarkis, J., & Sloan, T. (2012). Sustainable benchmarking of supply chains: The case of the food industry. *International Journal of Production Research, 50*(5), 1297–1317.

Zhu, J. (2014). *Quantitative models for performance evaluation and benchmarking: Data envelopment analysis with spreadsheets* (Vol. 213). Basel: Springer.

Zhu, Q., Sarkis, J., & Lai, K. H. (2012). Green supply chain management innovation diffusion and its relationship to organizational improvement: An ecological modernization perspective. *Journal of Engineering and Technology Management, 29*(1), 168–185.